

Improving Brain MRI for Early Tumor Diagnosis Using Deep Learning Generative Adversarial Networks: A Comprehensive Review

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Abstract: Brain Tumor is an abnormal growth of cells in the brain that grows rapidly, invades surrounding tissue, and is often life-threatening. Therefore, there is a need to improve Magnetic Resonance Imaging (MRI) for early tumor diagnosis using Generative adversarial networks (GAN). A comprehensive review is conducted in this study to discuss the related literature that improve MRI for early Tumor Diagnosis using recently developed GAN. We analyzed several methods that were conducted by these literature studies and created a brief classification. The key challenges associated with achieving high-accuracy Tumor Diagnosis were addressed also. The literature references had been identified from 4 good reputable Databases: IEEE XPLORE, Web of Science, Scopus and PubMed. Publications were taken in recent years, specifically 2020-2024, because the GAN technology was developed in 2014 and it was largely accelerated. We excluded the researches with irrelevant titles and also the papers on other Tumors in human body. This study was conducted between January and May 2025. Then, we summarized the results of the collected articles. We found 45 related articles, about 25 of them presented actual attempts to synthesize images and provide accurate segmentation/classification using single/multiple landmarks. The other 20 articles discuss the recent advances in GANs, do practical experiments, and contain analytical studies of Brain Tumor. As a result, set of recommendations were provided to improve Deep Learning GAN approaches to enhance MRI for early Brain Tumor diagnosis systems.

Keywords: Magnetic Resonance Imaging (MRI), Machine Learning (ML), Deep Learning (DL), Generative Adversarial Networks (GAN), Convolutional Neural Network (CNN)

1. Introduction

In recent years, medical research has made significant advances in the diagnosis and treatment of many diseases. However, there are still life-threatening diseases, such as Cancer, if not detected early, especially Brain Tumors. A Brain Tumor is a mass of abnormal cells that grow in Brain tissue. Tumors can be classified into two types (Benign or Malignant). Malignant Tumors are more aggressive and are known as Brain Cancer. The main types of Tumors are: Meningiomas, Pituitary Tumors, and Gliomas.

A Meningioma is a Benign Tumor that grows slowly on the outer covering of the Brain. The Pituitary Gland is located beneath the Brain. An abnormal growth around this gland is called a Pituitary Adenoma, and these Tumors are easy to detect. Gliomas are the most aggressive and have the highest mortality rate of all Brain Tumors [1]. They are difficult to detect because they grow in both halves of the Brain and the cells surrounding them. Statistically, approximately 121,000 people are diagnosed with Brain Tumors each year in the United States. While the World Health Organization records approximately 300,000 new cases of Brain Tumors worldwide. It can affect any age group, but Glioblastoma is more common in adults over 50 years of age, especially men [2]. Brain Tumors are rarely

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recognized in the early stages, and the skull bone restricts the space available for growth, so any new growth will increase intracranial pressure and is considered an early symptom of tumors. These symptoms of Benign Tumors vary depending on the location of the Tumor in the Brain, such as headache, vomiting, numbness in the hand or leg, or seizures. Neuropsychiatric symptoms such as anxiety, personality changes, memory disturbances, or anorexia nervosa are common in patients with meningiomas. When only psychological symptoms appear, the diagnosis of a meningioma may be delayed. Similarly, fatigue, seizures, edema, endocrine disturbances, and psychiatric disturbances are common symptoms in patients with gliomas. These symptoms are general and non-specific, and can be detected on imaging [1].

Common types of medical imaging are Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Photoemission Tomography (PET). Computed Tomography (CT and PET) has become modern Radiotherapy effective method that utilize X-rays for examination and provide high spatial resolution that makes it ideal for diagnosing Tumors. CT is inexpensive and requires short examination times, and requires contrast injection to increase image resolution. However, it faces the challenge of obtaining images due to the radiation emitted during imaging, which has harmful side effects that increase the risk of Cancer. In addition, the CT imaging has limited contrast for soft Tissues. In contrast, MRI is the most popular form of medical imaging because of its ability to diagnose soft Tissues such as Muscles, Blood vessels, and the Brain. This is achieved by creating sequential images with varying contrasts, providing realistic images with great detail and high resolution. However, it takes longer to produce medically accurate images [3]. However, the biggest challenge with MRI imaging lies in accurately identifying the Tumor's location due to its varying shape. This is crucial for providing treatment alternatives, such as Surgery, Radiation Therapy, or Chemotherapy, to increase the chances of survival [4]. Another challenge is that there is always a chance of medical error, which requires a high level of expertise and the ability to interpret images quickly, even in the early stages of the tumor. Furthermore, prolonged processing time can lead to significant image distortions due to patient movement, physiological movements, or sensitivity to contrast agents, which hinders the process of obtaining multiple sequences of patient images [5].

In recent years, researchers have shown great interest in proposing several Artificial Intelligence (AI) techniques, including traditional Artificial Neural Networks (ANN) and Machine Learning (ML) algorithms. On the other hand, Deep Learning (DL) algorithms have become pioneers in image processing across all fields, including Medicine, because they automatically generate and learn deep and complex features from input data. Numerous studies have been conducted on ML and precision learning, reaching levels that rival, and sometimes even outperform, the human mind in certain diagnoses. This has been achieved through object detection and tumor classification using multiple processing techniques for feature extraction, image enhancement, and noise discrimination [1]. Deep-level Convolutional Neural Networks (CNNs) have demonstrated an effective performance in object detection and processing. The use of deep neural networks has led to a qualitative leap in Tumor diagnosis, particularly Brain Tumors. This is done by introducing medical features into these networks to generate images and extract deep and precise features from them, as well as reconstructing the contrast in MRI images for missing or distorted data in a single step compared to traditional methods [6]. However, deeply connected CNNs are prone to imbalanced learning problems, which lead to a high incidence of false positives or false negatives, and the presence of more false branches than ground truth levels.

Tumor segmentation and enhancement suffer from diagnostic accuracy errors and inability to adapt to real Tumor images. This is because CNNs rely on pixel-level in target attributes to match real image with the image generated by the model. In addition, studies have shown that CNNs require massive and high-quality training data to achieve human-level success, which is difficult to obtain for all possible medical conditions. Medical data also requires expert expertise, which can lead to a lack of annotated data and underfitting, leading to significant errors in training and testing. Furthermore, images contain high levels of noise or distortion from different techniques or equipment, which can lead to variability in image quality and make it difficult to build a general CNN model capable of classifying all Brain Tumors [5].

Generative Adversarial Network (GAN), a type of unsupervised learning algorithm that has proven its ability to generate natural images that closely resemble real images. The GAN consists of two models: the Generator and the Discriminator. The Generator generates images that appear real but are faked to deceive the Discriminator. While the feature attempts to evaluate the realism of real and fake images, GANs have broad applications in all fields, including medicine. In recent years, GANs have become a powerful tool for improving and analyzing medical images, especially Tumors. This is done by improving the quality and accuracy of images and reconstructing medical images from data damaged or lost during medical examinations or through imaging equipment [1].

Several studies had been conducted on Brain Tumors that rely on optimization methods, segmentation, and classification techniques to determine contrast and define precise tumor boundaries. These techniques typically use foreground and background pixels to extract image features. These features are often sensitive to low contrast and their inability to extract deeper features of the disease [5]. Most of these technologies also face significant challenges, as they

require prior knowledge of the medical field and lack standardized data, which requires significant time to process and format using various software.

Therefore, it is important to build an early Brain Tumor diagnostic system supported by modern computer technologies to overcome these challenges. Therefore, there is a need to review the literature studies which are related to Brain Tumor diagnosis using GAN and analyze their strengths and limitations. According to this, we conducted in this work a comprehensive review for the literature studies related to improving MRI for early Tumor Diagnosis using recently developed GAN. We will discuss: their used methodologies and techniques; the strengths, limitations and the results of these studies. Finally, a set of recommendations were provided to improve Deep Learning GAN approaches to enhance MRI for early Brain Tumor diagnosis systems. The remainder of this work is organized as follows: Section 2 reviews the related studies; Section 3 presents the research methodology; Section 4 details the optimizing GAN for Tumor Diagnosis; Section 5 includes results and discussion; Section 6 details the topic challenges and suggested recommendations; and finally, Section 7 concludes this work with future research directions.

2. Related Literature

Many researchers had been used different GAN models to process medical Tumor images. In 2021, Wang et al. [7] developed a self-super resolution framework with cycle consistent GAN (CycleGAN). They used the learning-based method to synthesize high-resolution (HR) 3D Brain Tumor slice-level CT images from low-resolution (LR) 2D CT images. In 2024, Chang et al. [8] proposed a GAN model using diffusion probability modeling to generate high resolution (HR) MRI images from low resolution (LR) MRI images. They aimed to harness cutting-edge diffusion probabilistic deep learning techniques to create a framework for generating HR MRI from LR MRI, improving the uncertainty of denoising diffusion probabilistic models (DDPM). Their results for the prostate dataset, the Bicubic interpolation model (Bicubic), conditional GAN (CGAN), and their proposed DDPM framework improved the noise quality measure from low-resolution images by 4.4%, 5.7%, and 12.8%, respectively. And also enhanced the signal-to-noise ratios (SNR) by 11.7%, surpassing Bicubic (9.8%) and CGAN (8.1%).

On the other hand, researchers showed an interest in the super resolution feature using GAN models with multiple scales to improve high-resolution MRI images of Gliomas [9][10]. In 2022, Waqar et al. [9] proposed GAN based architecture for medical images, which maps low resolution medical images to high-resolution images. Their proposed architecture is divided into three steps. In the first step, they used a multi-path architecture to extract shallow features on multiple scales instead of single scale. In the second step, they used a ResNet34 architecture to extract deep features and upscale the features map by a factor of two. In the third step, they extracted features of the upscaled version of the image using a residual connection-based mini-CNN and again upscale the feature map by a factor of two. And, in 2022, Xianqi et al. [10] developed DL method based on GAN using Unet as generator network to upsample Magnetic Resonance Spectroscopic Imaging (MRSI) by a factor of 4. They trained ANN on simulated metabolic images from 75 glioma patients. They evaluated the performance of deep ANNs on MRSI data measured in 20 glioma patients and 10 healthy controls at 3T with a whole-brain 3D MRSI protocol optimized for detection of D-2-hydroxyglutarate (2HG). They used prior information from high-resolution anatomical Magnetic Resonance (MR) imaging. They compared the Super Resolution (SR) MRSI to ground truth by Mann–Whitney U-test of Peak Signal-to-Noise Ratio (PSNR), Structure Similarity Index Measure (SSIM), Feature-based Similarity Index Measure (FSIM), and Mean Opinion Score (MOS). Their results indicate that proposed DL methods are effective in enhancing spatial resolution of metabolite maps. Patient results suggest that this may have great clinical potential for image guided precision oncology therapy.

Image SR techniques based on DL can assist researchers in extracting spatial features from a low-resolution image captured with current technologies. In 2024, Priyanka et al. [11] used an updated variant of SR technique: Real Enhanced Super-Resolution Generative Adversarial Networks (Real-ESRGAN) to produce 2D real-world images with excellent perceptual quality. They investigated their suggested approach using four distinct medical image types: 1) brain MRI images from the BraTS dataset; 2) Dermoscopy images from the ISIC skin cancer dataset; 3) Cardiac ultrasound images from CAMUS dataset; and 4) Chest x-rays images from the MIMIC-CXR Dataset. Their employed architecture achieved improved visual results in comparison to the alternative innovative techniques for SR. Their results improved diagnostic accuracy and were used in targeted radiotherapy for tumors. On the other hand, researchers have overcome the difficulty of obtaining complete clinical information resulting from radiation reduction for brain tumor patients. In 2024, Yu Fu et al. [12] and in 2021, Yu Gong et al. [13] have developed multiple models using Multi Pareto Generative Adversarial Network (MPGAN) and Parameter-Transferred Wasserstein GAN (PT-WGAN) respectively to generate high-quality Positron

Emission Tomography (F-PET) images of human brain, remove noise, and fill in missing data from low-dose L-PET images without affecting the structural details of the image.

In 2021, Wanyun Lin et al. [14] adopted the Reversible GAN (RevGAN) model to reconstruct the missing data to take advantage of multi-modal complementary information. After that, they proposed a 3D CNN classification model with multi-modality input to perform AD diagnosis. They evaluated their suggested method on the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, and compared the performance of the proposed method with those using state-of-the-art methods. Their results showed that the structural and functional information of brain tissue can be mapped well and that the image synthesized by their method is close to the real image.

In 2024, Zhang et al. [15] proposed a GAN based on pyramidal attention mechanism to generate PET images through pyramidal attention mechanism and standard discriminators. This is to solve the problem of lack of PET data and complete the multimodal data sets of MRI and PET. It is also to combine the grey matter part of MRI images with the metabolic information in PET images to achieve multimodal medical image information fusion, and achieve classification and diagnosis of fused images through ANN. Their results achieved 89.9% accuracy. In 2021, Bin Tang et al. [16] and Xiaoning Liu et al. [17], and in 2022, Jiffy Joseph [18] and Jiangtao Wang et al. [19] have developed GAN, GAN Residual Network (ResNet) with CNN, Wasserstein GAN (WGAN), and Cycle Contrastive Unpaired Translation network (cycleCUT) models respectively. This is to generate enhanced synthetic computer tomography (sCT) images from MRI images similar to real Computed Tomography (CT) images of Brain Tumors [16-19]. Jiffy Joseph [18] developed a model using WGAN to merge medical images to generate SCT (synthesis CT) from MRI. They used the Wasserstein metric to calculate the difference between real and generated images at a granular level (Patches: small parts of the image) within the Discriminator, which helped improve the quality and accuracy of the generated image.

Purposed absorbed dose calculation in magnetic resonance-guided radiation therapy (MRgRT) is commonly based on pseudo CT (pCT) images. In 2022, Amir Jabbarpour et al. [20] investigated the feasibility of unsupervised pseudo-CT (pCT) generation from MRI using a cycle GAN (CycleGAN) and a heterogenous multicentric dataset. They generated pCT images from MRI images and calculated the doses of targeted radiotherapy using the CycleGAN model. They performed a dosimetric analysis in 3D conformal radiotherapy (3DCRT) planning. Two studies conducted using CycleGAN and GAN models with AdaLN to transform low-quality CT image features into high-quality CT images. In 2021, Serin Yang et al. [21] proposed unsupervised continuous kernel conversion method using cycle-consistent GAN (cycleGAN) with adaptive instance normalization (AdaIN). Monte Carlo (MC) dropout requires a large number of inferences runs, variable as a function of the particular uncertain feature. In 2024, Stephen Liu et al. [22] proposed a single-pass method – the Moment Propagation Model – which approximates the Monte Carlo (MC) dropout by analytically propagating the statistical moments through network layers, removing the need for multiple inferences and removing errors in estimations from insufficient dropout realizations.

In recent years, medical image fusion has become a leading DL field. In 2023, Safari et al. [23] have developed multiple models for fusion of MRI and CT images to remove noise and obtain a comprehensive and accurate representation of brain tumors. They used a Multi Model Medical Image GAN with a conditional competitive generative network (FACGAN) and frequency attention. Their results showed high accuracy in obtaining SCT images containing accurate information about the soft tissues of the brain, and proved its effectiveness in planning radiotherapy for Brain Tumors. CNN have shown remarkable performance in generating sCT images. CNN-based models tend to synthesize more low-frequency components and the pixel-wise loss function usually used to optimize the model can result in blurred images. In 2024, Kexin Wei et al. [3] proposed frequency attention conditional GAN (FACGAN) to address this problem. They designed a frequency cycle generative model (FCGM) to enhance the inter-mapping between MR and CT and extract more rich tissue structure information. Also, in 2022, Zhang et al. [24] used a GAN model to combine PET images with MRI images. This removed noise from the PET images and filled in missing MRI data. The MRI was then used as an input image, with the inclusion of the PET image as a condition to improve performance for PET images with high diagnostic accuracy. Many studies have been conducted to deal with noise and missing data in MRI images of brain tumors. In 2021, Jun Lv et al. [25] compared four GAN models: RefineGAN, KIGAN, RecoGAN, and DAGAN, to deal with missing data. The study demonstrated that the RefineGAN model has high accuracy and quality for generating MRI images. Whereas, in 2021, Weimin Zhou et al. [26] developed two models: 3DProAmGAN, which is capable of generating random 3D models from measurements in medical imaging techniques, and StyAmGAN, which can manipulate fine details of soft tissues in the brain. These are both improved models of the AmbientGAN network. Both models demonstrated high quality and accuracy in generating MRI images to diagnose fine details of Tumors.

In 2022, Weimin Zhou et al. [27] proposed GAN that employs AmbientGANs with modern progressive or multiresolution training approaches to generate high-quality medical images from images with noisy and incomplete

measurements. They validated the AmbientGANs in a controlled way using computer-simulated MRI data corresponding to a stylized imaging system. In 2021, Geng et al. [28] used a GAN with the content-noise complementary learning (CNCL) strategy, in which two DL predictors are used to learn the respective content and noise of the image dataset complementarily. They presented a medical image denoising pipeline based on the CNCL strategy and implemented as a GAN, where various representative networks (including U-Net, DnCNN and SRDenseNet) are investigated as the predictors. They validated the performance of these models on medical imaging datasets including CT, MR, and PET. The results proved that the strategy is effective and accurate in improving images, removing noise, and assisting in medical diagnoses. In addition, numerous studies have been conducted to generate high-resolution contrast-enhanced CT and MRI images. This is to reduce imaging time while minimizing patient exposure to radiation, which increases the risk of tumors, using GAN and GAN-ST models, respectively. These proposed studies have demonstrated the accuracy and quality of medical images in a shorter time, resulting in significant medical and economic benefits for the patient [5, 6, 29-32]. On the other hand, many studies have been conducted on the accurate classification and segmentation of brain tumors, which is important for improving healthcare and making rapid treatment decisions.

In 2021, Cong [33] proposed a semi-supervised GAN network to generate stain-normalized images to integrate source images and unify stains without the need for actual corresponding data. The Staining in medical imaging is considered an important and effective tool for the diagnosis and treatment of brain tumors. Whereas, in 2021, Changhee et al. [34] proposed an unsupervised medical anomaly detection model using GAN (MADGAN), and they reconstructed MRI images of adjacent brain areas to detect abnormal tissue variations from the images, which helped in accurately and rapidly discovering and classifying cases of brain tumors. In 2022, Bilal et al. [1] classified MRI images of Brain Tumors using the Variational Auto-Encoder (GAN-VAE) model with an accuracy of 98%, making it a useful clinical tool for specialists [1]. This is done to enhance MRI brain images using ResNet50 and also utilized a Noise Vector instead of traditional random noise to improve the Mode Collapse issue that usually occurs during training.

Researchers have also classified Brain Tumors using the SAGAN model using multiple MRI image techniques with an accuracy of up to 99% while reducing computational time. Researchers have also used a GAN-NAS network with neural standard searches to improve multiple Brain Tumor classifications [35, 37]. In 2024, Wang et al. [38] conducted on segmenting brain tumors to improve diagnosis and assist physicians in radiological planning. The researcher used a GAN network to automatically segment CT images with high accuracy. Several studies have also been conducted on segmenting MRI images of brain tumors. Researchers developed a study using the Vox2Vox model for multichannel images [39]. Other researchers have presented studies using multiple criteria to augment the data generated by GANs. They used VAE-GANs to segment gliomas with high accuracy [2, 4, 40-42]. Some researchers have proposed a hybrid GAN-NADE-K model that combines GAN with neural probability distribution. In 2023, Changjuan et al. [42] used VAE-GAN for the segmentation of Brain Tumors in patients who underwent surgery, as the model achieved high-quality segmentation of MRI images both before and after surgery.

Several algorithms have also been combined to improve brain tumor segmentation in MRI images. Other researchers have developed the DeepResidual network with the Bat algorithm. Others have proposed the SSIMDCL model for obtaining high-resolution images, and the CTGAN model for improving the classification and segmentation of brain tumors with high accuracy. This is done by using advanced diffusion mechanisms with modern algorithms that significantly reduce processing time [43-45]. GAN had been developed firstly by Goodfellow et al. [46]. They pioneered DL by developing the GAN, as a type of unsupervised learning algorithm. Many researches [47]..[54] conducted GAN as one of the DL methods for classified, diagnosis and enhancement of digital medical images. In 2025, Thaer Kadhim [47] conducted DL CNN for image processing for automated mammography analysis and breast cancer detection. In 2025, Serri Hamad [48] utilized CNNs for the identification of lung cancer. In 2026, Samaa Ghanim [49] adopted Hybrid ResNet50 and DenseNet121 with adaptive weighted feature fusion in infectious chest diseases classification. In 2025, Shms Aldeen [50] adopted multimodal fusion DL for improving heart disease classification. In 2026, Mohammed Yousif [51] enhanced the classification of Diabetic retinopathy using hybrid efficientNetB0 with CBAM. In 2025, Atyaf Yaseen [52] conducted CNN models on fundus images for detection of diabetic retinopathy. Whereas, Mohamed Abdkhaleq [53] used hybrid DL and Neuro-Fuzzy approach for diagnosing COVID-19 using CT scan imaging. This is done by integrating CNN, ANFIS, and PCA. Finally, in 2025, Noor Younis et al. [54] conducted a review of AI Techniques such as DL, CNN and GAN. for Medical Image Enhancement.

3. Research Methodology

3.1. Studies Selection Procedure

The method for choosing appropriate studies was on the basis of 2 stages: screening and filtering. Successively, both stages met the same criterion for inclusion and exclusion. Both duplicates and unrelated studies by title and abstract skimming were omitted during the first stage. Then, the result in a set of papers was entirely read, analyzed, and summarized in the filtration stage. This work was carried out between January and May 2025. Various keyword combinations were used in the search of highly reputable libraries (IEEE Xplore, Science Direct, PubMed, Scopus, and Web of Science). Fig.1 shows the study selection, research query and inclusion criteria used in this work. Our search query consists of 2 parts that are connected with each other using operator "and". The following set of keywords ("Brain Diseases", "Brain Tumor", "MRI") and ("Receptive field," "Loss function", "GAN", "Generative Adversarial Network", "Deep Learning", "Convolutional Neural Network", "CNN", "Encoder") belong to the first and second parts, respectively. The operator "or" is used to connect keywords within the same part. Based on this, our study scope is formulated. The quest focused on different Journals and Conferences and omitted Books and all other forms of literature. Therefore, we mainly concentrated on up-to-date and applicable scientific studies related to the use of GANs in Brain Diseases, especially Brain Tumor. The full text reading includes 70 papers: 5 researches are related to PET; 27 researches are related to MRI; 7 researches are related to MRI and CT; and 20 researches are related to CT; and finally, 11 researches are global. After excluding 25 articles, the final number of included articles are 45: 5 researches are related to PET; 24 researches are related to MRI; 7 researches are related to MRI and CT; 6 researches are related to CT; and 3 global researches.

3.2. Related Studies Analysis

Through studying all the researches, 98 keywords were counted to serve as significant keys for the keywords in the study. The keywords were described according to their frequency in all the research studies, which showed that there are 15 common keywords across all researches from a total of 98 keywords with a minimum frequency of 2. In comparative analyses, it was found that there are keywords that repeated at least twice in all studies. Fig.2 illustrates the factors of the keywords through the connections of the common keywords with each other. The size of the rectangle indicates the frequency of the keyword; the larger the size of the rectangle for a keyword, the more frequently it appears in studies as a primary factor.

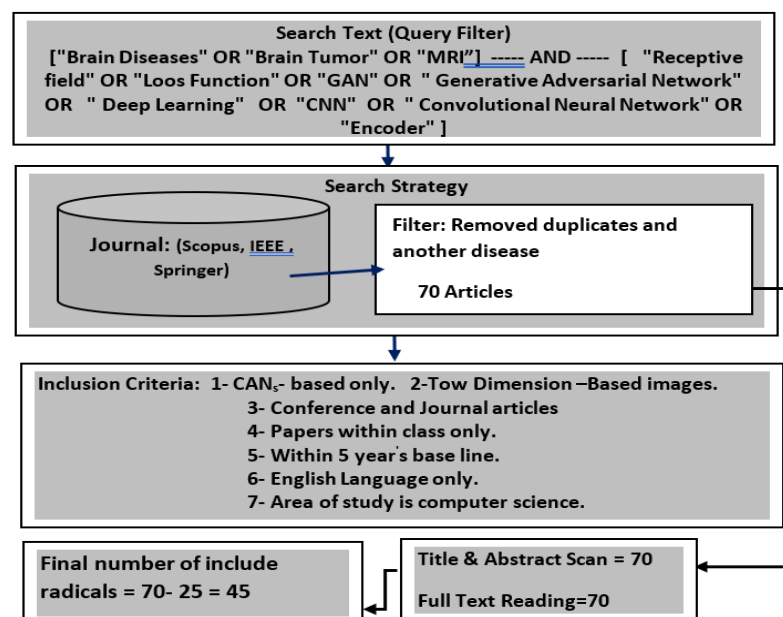


Figure 1. Research query and criteria used in this work.

The second factor is the strength of the connection between keywords; as the thickness of the link increases, the keyword frequency in the same study also increases. For example, the keyword "GAN" has the largest rectangle size and is considered a primary level in keywords, meaning it is the most frequently mentioned in research. In contrast, the frequency of keywords decreases for lower levels, as indicated by the smaller size of the rectangle based on their occurrence in the research. The links between the keyword "GAN" and "DL", "GD", "BT" are thick, meaning these keywords appear frequently together in studies related to Glioblastoma detection. Meanwhile, there are thinner links between "GAN" and the

keywords "HR", "MEI", "BS", indicating that they were used in separate studies less frequently. Table1 shows the frequencies of keywords appear in Glioblastoma detection studies.

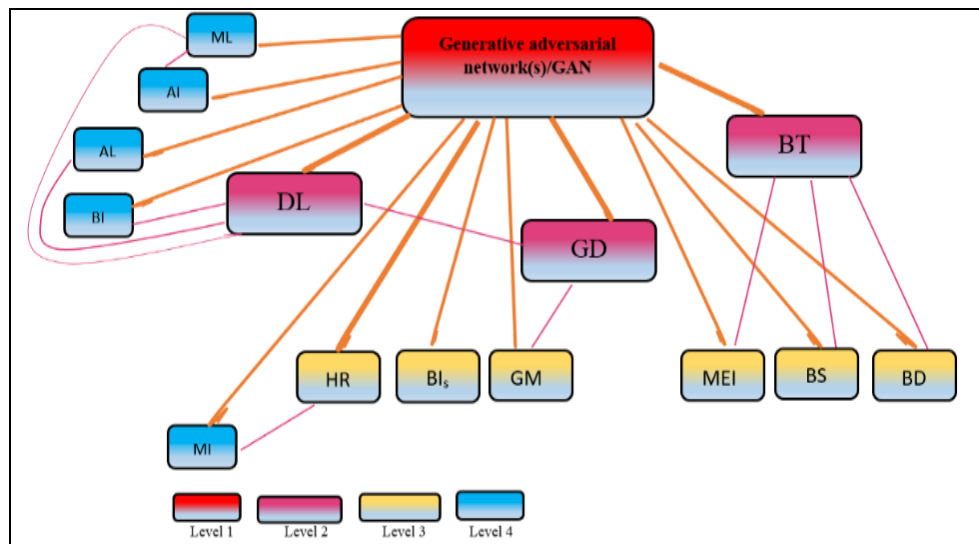


Figure 2. Factors of the keywords through the connections of the common keywords with each other.

Table 1 shows the frequencies of 15 keywords appear in Glioblastoma detection studies. Table 1 shows that the keyword "GAN" was the most frequent, appearing 22 times alone and 23 times with other keywords. Similarly, the keyword "DL" appeared 21 times alone and 22 times with other keywords, while the keyword "GD" appeared 9 times alone and 11 times with other keywords. The results of the query showed that the keywords received the highest scores in all researches for the specified time period of the study and indicated that the highest occurrences of the three main keywords: "GD", "DL", and "GAN" had the strongest appearance and connections.

3.3 Taxonomic classification of GAN Methods

This section includes the Taxonomic classification of GAN Methods for Brain Cancer diseases for all studies. The total number of studies obtained from the scientific research process is 70 studies for the period from 2020 to 2024 from global publishers with high impact factor journals such as (Web Sciences, IEEE, Scopus). Through reviewing these studies and based on the selected keywords, 35% of the studies were excluded, which amounts to 25 studies. Some of them did not utilize GAN networks, while others used GAN networks to generate images for diseases other than brain cancer. Additionally, some were irrelevant to the topic. As for the remaining studies, which is 65%, equivalent to 45 studies, all rely on deep learning and the use of various types of GAN networks.

Table 1. Frequencies of 15 keywords appear in Glioblastoma detection studies.

	Keywords	Freq.	Total link strength	Level
Techniques	DL	21	22	2
	GAN	22	23	1
	AI	4	4	4
	ML	4	4	4
	High Resolution (HR)	5	5	3
Diseases	Brain Tumor (BT)	5	6	2
	Brain Diseases(BD)	4	5	3
	Glioma Diseases (GD)	9	11	2
Imaging	Brain Image (BI)	4	5	4
	Medical Imaging (MI)	4	4	4
Papers' contribution	Adversarial Learning (AL)	3	4	4
	Brain Segmentation (BS)	4	5	3
	Medical Enhancement Image (MEI)	4	5	3
	Generative Models (GM)	4	4	3
	Brain Image Synthesis (BIs)	4	4	3

A comprehensive study has been conducted on the final remaining number of research studies to develop methodologies for studies during these years, and what are the real attempts to develop various Network architectures for GAN networks, organizing weights within them, new loss functions, weight reduction, and improving medical images through various operations for enhancement, segmentation, and classification to detect brain cancer in its early stages and assist in speeding up the diagnosis to provide therapeutic and radiological services to affected patients to increase survival chances.

However, there are still new areas in deep learning technologies. These studies also indicated that there are potential future constraints and challenges for deep learning through GAN network models for rapid improvement and early detection of cancer and the possibility of finding solutions to those potentials. Fig.3 presents the taxonomic classification of GAN-based methods and models for Brain Cancer diseases across all literature studies from 2020 to 2024. This is according to the optimization architecture's structure, categorized into (6) groups based on the optimization methods. Four of these groups focus on image enhancement methods to obtain high-resolution medical images from low-resolution and blurred images, and two of them are dedicated to classification, segmentation, or a combination of both for medical images. Through these groups, the following were identified:

- Determination of feature discrimination levels (PixelGAN, PatchGAN or ImageGAN),
- The number of classification and segmentation parameters (single or multiple),
- The architectures or structures used in different GAN networks across all studies (Cycle-GAN, Pix2Pix, CGAN, WGAN, DCGAN), and
- The contribution of each such as enhancement [H], segmentation [S], classification [C], or synthesis [Y].

The studies are categorized into 6 consecutive groups using various GAN networks for all brain cancer diseases to improve medical images. The enhancements included multiple types through (Enhancement, Classification, Segmentation, Synthesis, and a Mix of all of them). The methods to deal with the descriptors included (PixelGAN, PatchGAN, ImageGAN), and the features used in enhancement, classification, and segmentation included Single and Multiple. Moreover, the specific type of GAN used will be clarified later.

On the other hand, there were criteria for excluding studies: those that are outside the scope of the topic, or those that develop models using ML networks, or those that use traditional optimization methods. All analyses of the studies were compiled into a single Excel file for the purpose of quick reviews, containing all the analyses and notes about any study by reading the study and extracting the models used, the database, the evaluation methods, the results achieved by each study, the challenges faced, as well as the development of each work through future works.

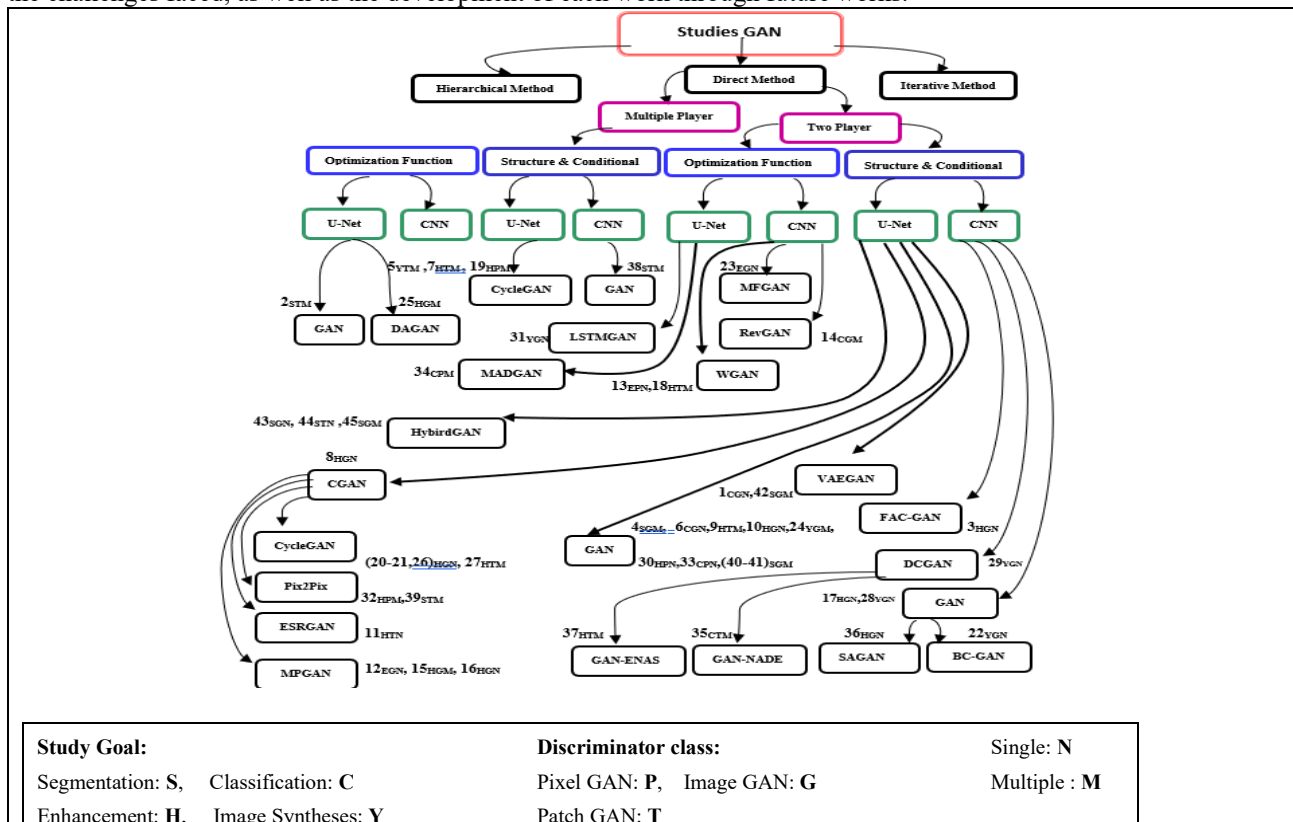


Figure 3. Classification of the Taxonomy of the literature

3.4. DL GAN Development Studies

Since the development of GAN in 2014 by the scientist Goodfellow, and his colleagues [46], researchers have been continuously trying to develop and improve GAN using various methods: weights; updating the loss function; and integrating them; developing architecture categories and integrating them). It remains a research area for many studies and the challenges it has faced during the developmental periods of DL. Many researchers interested in this field have begun to develop multiple models to improve images of brain diseases, including enhancement, classification, and segmentation, including Brain Cancer, with the latest being the study area for years (2020-2024). It is noted in Fig.3 that many studies have developed GAN models. This development is classified into four levels:

- The first level is based on the method used (direct, hierarchical, or iterative), where it was observed that studies (1-45) relied on the Direct Method.
- As for the second level, studies are classified based on the number of players (generator, discriminator), which can be with two or three players or more players. Studies that were classified with two players were based on 1 Generator (G) and 1 Discriminator (D). Other studies classified with more than one player had different G or D aimed at solving training problems and instability of models, while the level was classified.
- The third is based on the Architecture Category, which addressed the studies from two aspects (Optimization Function and Structures or Condition), and each one of them was classified at the fourth level based on the Generator backbone environment, based on (U-Net based or CNN based), respectively.

Analysis of the studies revealed that the majority followed the Direct Method and did not use the Hierarchical or Iterative approaches. These methods provided opportunities for studies in the field of brain cancer detection. The studies using the Direct Method, which were classified based on the number of players at the second level, accounted for approximately 39 studies out of a total of 45 that used two players (1G, 1D). What remains of the studies is that 6 developed their studies through multiple players [2, 5, 7, 19, 25, 38]. Carver et al. [2] developed a GAN network to improve the segmentation of multi-parametric images (MRI) with different contrasts and three players (1G, 2D). The developed model showed high accuracy in producing high-quality SyMRI images for multiple parameters, which helped address the deficiencies of parameters for medical images.

Whereas, Wang et al. [7] developed a CycleGAN model with (1G, 2D) using 2D-CT slices of brain levels to reconstruct high-resolution three-dimensional CT images. While, Jun, Jin and Guang [25] reduced patient motion artifacts in MRI images by comparing four types of GAN networks: (DAGAN, ReconGAN, KIGAN, and RefineGAN), achieving a speed-up in MRI image generation by (2, 4, 6) times using a random Under Sampling Mask, and the RefineGAN method achieved high accuracy for MRI image reconstruction.

In the year 2022, Huang et al. [5] developed a Dual Directed Reinforcement Network model (PIDD-GAN) for MRI images by using Parallel Multi-Angle Imaging with a Dual-Discriminator feature. Discriminator D1 was used to enhance the image edges and D2 for image reconstruction, resulting in high-quality improvement while reducing the time taken for MRI image reconstruction. Similarly, Wang et al. [19] developed the CycleCUT model, which is one of the types of GAN networks and possesses advanced features by generating CT images from MRI images of brain cancer. They used multiple players (2G, 2D) with different loss functions (Many loss: Cycle Consistency Loss, Identity Mapping Loss), where the model utilized contrastive learning to guide the generator to produce a high-resolution image similar to the original image while preserving the important characteristics of the original image. On the other hand, Wang et al. [38] divided CT images of brain tumors using a Multi-Players GAN model in cases where MRI images were not available to assist in radiation therapy. This is illustrated in Table 2.

The majority of the studies, as shown in Fig.3, numbering 39, focused on the use of 2 Players (1G, 1D). The researchers relied on the Network Architecture Category with both types (optimization function and structures or condition), of which 6 developed their models relying on the optimization function. In the remaining 33 researches, the researchers relied on structures or condition in developing their models. Whereas, the researchers [13, 14, 18, 23, 31, 34] were focused on improving and classification of medical images MRI, CT, PET or combined them for Brain Tumors. This is done using (U-Net or CNN) to develop different models of GAN networks.

Table 2. Studies Related to Multiple Player GAN

	Algorithm	Research No.	Research year	Type GAN	No. Players	Input Images	Output Images	Study Goal
1	U-Net	2	2021	GAN	1G, 2D	MRI	MRI	S
2	U-Net	7	2021	CycleGAN	1G, 2D	2D CT LR	3D CT HR	H
3	U-Net	25	2021	RefineGAN		MRI	MRI	H
4	U-Net	5	2022	PIDDGAN	1G, 2D	MRI	MRI	Y

5	U-Net	19	2022	CycleCut	2G, 2D	MRI	CT	H
6	CNN	39	2024	GAN	2G, 2D	CT	MRI	S

4. Optimizing GAN For Tumor Diagnosis

4.1 LSTM-GAN Model

Mohsen et al. [31] proposed the LSTM-GAN model as end-to-end deep learning NN that synthesizes CTP images to generate computed tomography perfusion CTP images. It is also to reduce the imaging time that exposes the patient to ionizing radiation without going through steps that increase the risk of brain cancer. Further, this LSTM-GAN model does not require the full CTP time series and can generate CTP maps using fewer time points. By reducing the scanning sequence from approximately 40 to 9 time points, this model can shorten scan times and reduce patient exposure to CT radiation. Their evaluations using the ISLES 2018 challenge Dataset, which includes 63 patients, demonstrated that the model can produce CTP maps using 9 snapshots without AIF selection, achieving an accuracy of 84.37%.

4.2 Unified-GAN

Yang Lei et al. [6] used a Unified-GAN network with multiple parameters for contrast in MRI images to enhance them, where the improved model demonstrated accuracy in transformations and the quality of the generated images matched the original images.

4.3 3D-GAN Network

Kermi et al. [41] developed a model to locate Brain Tumors using a 3D-GAN network to segment high-grade and low-grade Gliomas for multi-modal MRI images. They showed significant efficacy in accelerating Tumor diagnosis, thereby assisting doctors in treatment planning. Given the substantial challenges of Brain diseases, especially in locating tumors and their constantly changing shapes, a high level of expertise is required for the segmentation process.

4.4 GAN U-Net or CNN with 2 Players

About 33 of the selected literature studies (from 2020 to 2024) are focused on using U-Net or CNN architecture with 2 Players (1G, 1D), or the combination between them. This is to overcome the challenges in the diagnostic segmentation of Brain Tumors and the difficulty of collecting medical data due to the information confidentiality. Some researchers developed hybrid models by integrating different models with methods that speed up training and improve segmentation and classification of medical images for rapid detection of Tumors and facilitate treatment. Researchers [4, 6, 9, 10, 24, 30, 33, 40, 41] used the GAN-U-Net NN with different parameters. In 2022, researches [9, 10, 24] aimed to improve Brain Tumor images using a GAN- 2 Players NN (1G, 1D).

On the other hand, Weigand-Whittier et al. [30] developed a transfer chemical saturation-oriented generative model (Saturation Transfer GAN) to reduce the time required to obtain 3D MRI and to efficiently and accurately determine the chemical parameters without losing important details in areas that containing brain distortions due to tumors, thus achieving a High-Resolution Image (MRI). Whereas, Navid and Mustafa [4] developed unsupervised Learning GAN model and combined it with supervised learning. This is done to address the significant challenge of Tumor location due to its continuously varying shape, which requires a high level of expertise in image segmentation. GAN was used to augment image data for training, employing U-Net during the segmentation phase to effectively combine the remaining blocks. Their results achieved an accuracy of 0.94, indicating that the proposed model is effective and comprehensive for any image data in segmentation and diagnosis of tumors. Fig.4 shows the general structure of GAN for MRI data generation. In this system, the result ultimately depends on Discriminator decision, and the Discriminator network's output is related to the loss functions. A GAN network has two cost functions: generator cost and discriminator cost. Both of these costs are defined based on the discriminator error. The overview of cost functions used in GAN network is shown in Fig.5.

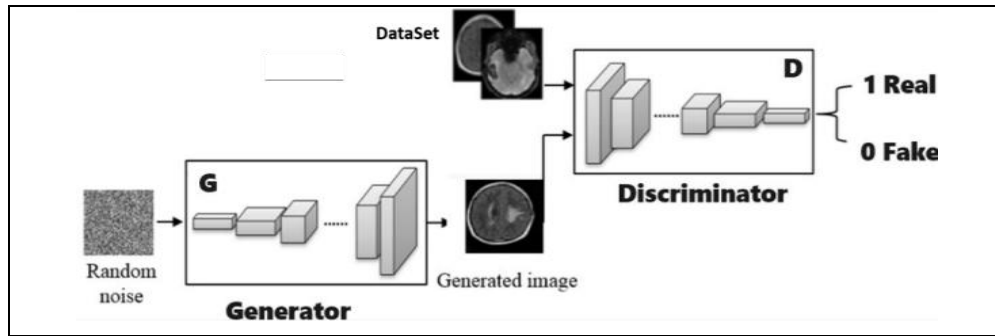


Figure 4. Structure of GAN for MRI data generation [4]

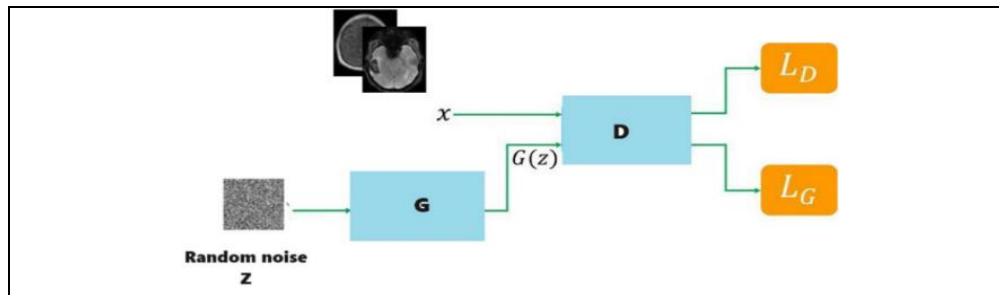


Figure 5. Cost functions in GAN network [4].

Many studies [17, 22, 28, 36] adopted GAN-CNN with 2 Players (1G, 1D). Liu et al. [17] and Stephen Liu et al. [22] utilized a GAN network to enhance medical images in 2021. However, the difference between the two studies is that Liu et al. [17] generated SCT images from MRSI contrast images for radiotherapy planning of tumors and compared them with traditional radiotherapy planning. Meanwhile, Senthil Pandi et al. [36] conducted a study to classify Brain Tumors through a GAN model and utilized Self-Attention mechanism to improve the quality of generated images by focusing on certain parts of the image based on the relationship between pixels in distant areas of the image (Global Pixel) instead of relying on adjacent local pixels (Local Pixel). They also achieved accurate and high-quality classification of brain tumors in less time. Also, other researchers [3, 29, 35, 37] developed models through structure and conditional with CNN.

Reddy et al. [29] diagnosed brain tumors by generating a variety of realistic additional images for CT and MRI to fill all types of gaps and distortions using DCGAN (Deep Convolution GAN) and a suitable objective function that improved the image classification accuracy to 98.5%. Whereas, Jayesh et al. [35] developed a model using powerful techniques and pre-trained models such as ResNet152, Efficient-NetB7, and CNN for extracting features from CT images. The developed model was a combination of GAN and NADE (Neural Autoregressive Distribution with CNN), where NADE estimated the probabilistic distribution of the data through an autoregressive prediction method. They also used the Maximum Variance Unfolding (MVU) technique, which is a nonlinear dimensionality reduction method aimed at projecting high-dimensional data into a low-dimensional image space while preserving the distances between close neighbors as much as possible, while at the same time trying to increase the distance between far points. This makes the true structure of the data more apparent.

Kexin Wei et al. [3] developed model-based CNN and addressed the issue of the loss function that leads to distorted images through a conditional generative adversarial network with Frequency Attention Condition (FACGAN), and their results produced high-quality SCT images while maintaining the fine details of brain images. Meanwhile, Zaitoon et al. [37] developed a model for classifying brain tumors using GAN+NAS (Neural Architectures Search) by searching for the best neural architecture design for the models, and they employed Adaptive Computation Time Transformers in their studies, which helped adjust the number of transformer layers based on the complexity of the input data, thereby enhancing the model's ability to handle complex tumor data.

4.5 Cycle-GAN (CGAN) with U-Net

Jabbarpour et al. [20], Serin Yang et al. [21], Zhou et al. [26], and Zhou et al. [27], separately, developed Cycle-GAN models with different architectures based on U-Net. Meanwhile, Zhou et al. [26] and Zhou et al. [27] proposed the Ambient-GAN model for generating high-quality MRI medical images from distorted and highly noisy images with different features, proving these models to be promising for establishing random models from medical measurements. Leizi

Li et al. [32] and Marco et al. [39] introduced conditional models through the Pix2Pix model. Marco et al [39] tried to segment Brain Tumors into Multi-Channel 3D-MRI images with high accuracy, and effectively measuring the total Tumor extent between the segmented and original images. Fig.6 shows the Generator Model and Fig.7 shows the Discriminator Model.

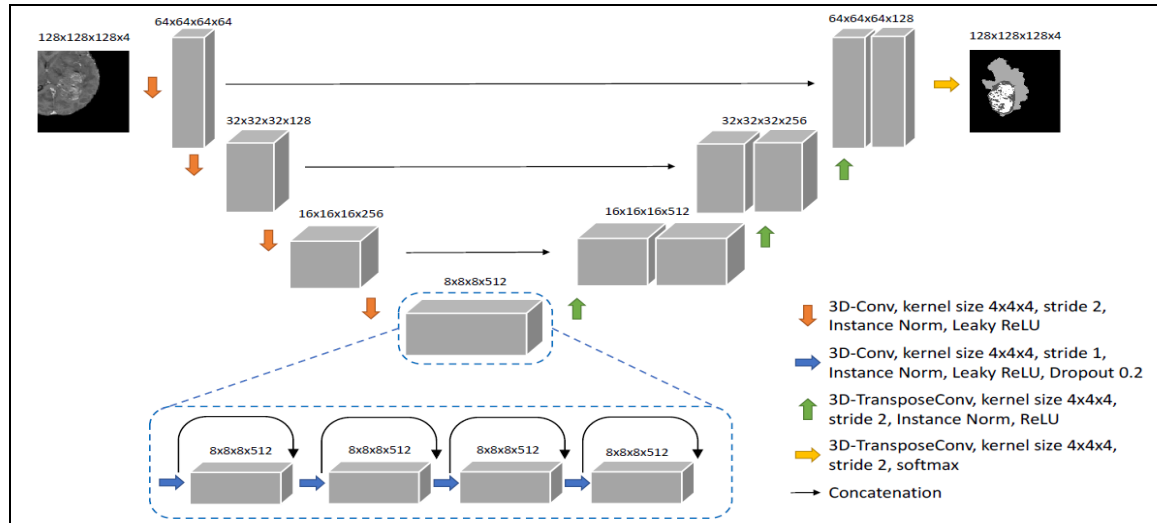


Figure 6. The Generator Model [39]

4.6 Hybrid GAN

Researchers [12, 15, 16] developed conditional MPGAN models by building models with different parameters. In recent years, there have been hybrid studies (Hybrid-GAN) used for the segmentation of MRI images of gliomas [43-45]. Vimal and Vimal [43] used the Deep Residual Network model with the improved invasive bat algorithm IIB (Improved Invasive Bat), which combines the Bat Algorithm (BA) with the Improved Invasive Weed Optimization (IWO) algorithm to enhance MRI image segmentation, resulting in a high accuracy of nearly 95% in early tumor detection. Meanwhile, Sara et al. [44] developed the SSIMDCL (Supervised Sim DCL) model to improve the segmentation of 3D-MRI images and compared it with several methods: CycleGAN, SimDCL, CUT, Faster CUT, and the model demonstrated high accuracy in segmenting MRI images.

Whereas, Nadenlla and Muneeswari [45] presented using the ERSACA-NET model through the Residual Structure framework and the Adaptive Channel Attention Mechanism. They used BCTSO (Binary Chaotic Transient Search Optimization) algorithm to select the most relevant features from shape and color to reduce complexity. Also, CTGAN method was used to address the class imbalance that occurs when there is an unequal number of images for each type of Tumor. The model achieved improvement compared to other methods with a processing time of 5-11 seconds, which is much faster than other models, and its strong performance opens up the possibility for more accurate and reliable classification of Brain Tumors.

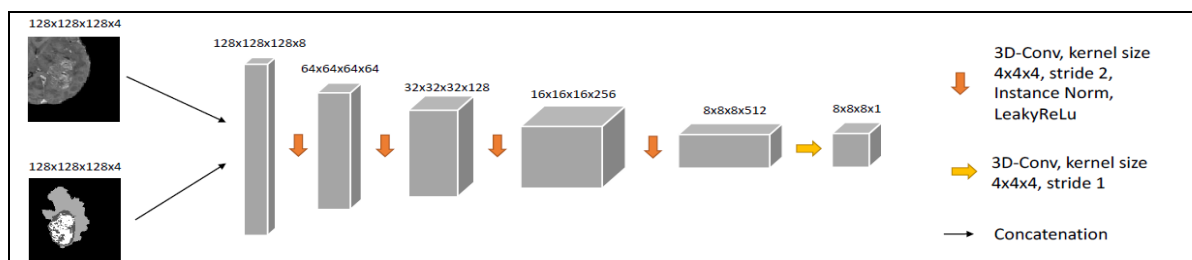


Figure 7. The Discriminator Model [39]

5. Results and Discussion

This study aimed to provide a summary of studies related to the detection of Brain Tumor, in terms of improvement, classification, and segmentation using GAN approaches. It highlighted the recent trends undertaken by researchers in this field, and systematically classified all relevant studies from 2020 to 2024 (Fig.3), as these years witnessed a technological revolution in image generation through GAN networks, helping to guide future research. The benefit of classification was:

- Organizing studies into a single framework facilitates understanding of related researches work.
- Helping to sort studies within interconnected frameworks that are easy to understand.
- Providing deeper insights for researchers on the subject, aiding in identifying gaps and challenges, and opening new horizons for researchers.
- Highlighting the strengths and weaknesses in related studies.

Studies [1, 6, 42] discussed generative models with Adversarial Autoencoders (AE) to improve the quality of generated images and identified the relationship among them. Some studies used data preprocessing techniques such as data augmentation or defining the Region of Interest (ROI), and automatic color adjustments [9, 10, 33, 37, 45]. While others conducted post-processing like image reshaping and contrast enhancement for tissues, which is crucial in disease diagnosis [2, 24]. Additionally, studies have presented Tumor detection through enhancing generative contrasts [6, 16, 30, 32, 34, 39, 42]. Table 3 shows the differences between selected studies in period of 2020-2024 focusing on Brain Tumor segmentation and enhancement, concentrating on types of MRI images during the development phase.

Table 3. Selected Studies Focusing on Brain Tumor Segmentation and Enhancement

	Algorithm	ResearchNo.	Pub. Year	Type GAN	No. Players	Input Images	Output Images
1	U-Net	[2]	2021	GAN	2-Player	MRI	MRI
2	U-Net	[39]	2021	Pix2Pix	2-Player	3D MRI	3DMRI
3	U-Net	[40]	2021	GAN	2-Player	MRI	MRI
4	U-Net	[41]	2023	GAN	2-Player	3D L-MRI	3D H-MRI
5	U-Net	[42]	2023	VAE-GAN	2-Player	MRI	MRI
6	U-Net	[43]	2023	Hybrid GAN	2-Player	MRI	MRI
7	U-Net	[44]	2023	Hybrid GAN	2-Player	3D MRI	3DMRI
8	U-Net	[4]	2024	GAN	2-Player	MRI	MRI
9	CNN	[38]	2024	GAN	2-Player	CT	MRI
10	U-Net	[45]	2024	Hybrid GAN	Multiple Players	MRI	MRI

Marco et al. [39] used a network to segment Tumors through a multi-channel Pix2Pix model for 3D-MRI images, which demonstrated its accuracy between the segmented images and the original image of the total Tumor. During year 2023, many studies [41- 44] aimed at developing the process of Brain Tumor segmentation due to its significant importance in this field. However, Reference [42] faced difficulties in locating Tumor with limited image data. Despite the existence of DL models specifically for Tumor segmentation, they still heavily rely on training data or data from healthy patients or pre-surgery, which led them to generate post-surgery MRI image data using VAE+GAN, achieving very high performance. Researches [43- 44] used hybrid models (Hybird-GAN) for segmenting MRI images of Gliomas.

Additionally, study [38] to generate MRI images from CT scans in cases where they were not available. They utilized GAN alongside Mask R.CNN to segment Gross Tumor Volume (GTV), which is the important part of the visible and measurable Tumor and is crucial for accurately determining the location for radiotherapy planning. This greatly assisted doctors in segmentation and radiotherapy planning with high precision. Whereas, studies [5, 6, 29-32] focused on algorithms (GAN, CGAN, CycleGAN, Pix2Pix) aimed at reducing time and costs for improving generated images using (2) players G, D or MultiPlayers. Their results were of high accuracy in less time, which contributed to speeding up diagnosis and providing radiotherapy for patients, as shown in Table 4. On the other hand, Table 5 shows the models architectures, datasets and challenges of literature studies related to MRI Image classification.

Table 4. Studies Related to Decreasing the Time for Image Syntheses and Enhancement

	Algorithm	Research No.	Research year	Type GAN	No. Players	Input Images	Output Images
1	U-Net	[6]	2020	GAN	2-Player	MRI	MRI
2	U-Net	[29]	2021	DCGAN	2-Player	CT, MRI	CT, MRI
3	U-Net	[5]	2022	CycleGAN	Multiple Player	MRI	MRI
4	U-Net	[30]	2023	GAN	2-Player	3D L-MRI	3D MRI
5	U-Net	[31]	2024	LSTM	2-Player	CT	MRI
6	U-Net	[32]	2024	Pix2Pix	2-Player	MRI(LR)	MRI (SHR)

Table 5. Architectures, Datasets and challenges of studies related to MRI Image classification

Ref.	Architecture	Dataset	Challenges
[25]	DAGAN, ReconGAN, RefineGAN and KIGAN	(1) Calgary–Campinas brain MRI dataset, (2) Stanford knee MRI dataset and (3) Private liver MRI dataset	Methods remains limited because models have not trained on the same datasets and validation strategies may be different.
[32]	GAN model (pix2pix)	BraTS2021 (T1W, T2W, FLAIR, and T1CE (size: $240 \times 240 \times 155$ voxels))	Not feasible to include all the dataset to make results more reliable.
[36]	BTC-SAGAN-CHA-MRI	BRATS dataset	Often lack precision and require substantial computational time.
[23]	MedFu- sionGAN	GLIS-RT, 230 patients: different brain tumor types underwent 3D T1-Gd, T2-fluid-attenuated inversion recovery MRI sequences, and a CT scan under different.	conventional image fusion methods necessitate source images to be perfectly aligned; otherwise, fusion images may exhibit undesirable artifacts known as
[37]	SPBTGNS model: GAN, NAS, ACT, SENET, and ENAS	Br35H, Kaggle Brain Tumor Dataset+ IEEE Data Port Dataset	variations in precision across different dataset sizes
[5]	Parallel imaging coupled dual discriminator (PIDD-GAN) for fast multi-channel MRI reconstruction	Calgary Campinas multi-channel dataset, MICCAI 2013 grand challenge single-channel dataset	Some remaining limitations. Dual discriminator superiority reduces for high down sampling percentage, and single discriminator structure.
[41]	3D-GAN	BraTS'2022 training datasets, containing 5880 brain MRIs corresponding to 1470 different subjects with HGG and LGG of various sizes, forms	Small Dataset, and brain cancer diagnosis, until nowadays, challenging because of variations in location, form, and imaging intensity of gliomas.
[18]	(WGAN) with a residual UNet	NVIDIA Tesla V100 GPU	Small dataset
[19]	cycleGAN	-	Limitation of GPU memory and small dataset
[45]	ERSACA-Net	Kaggle(BraTs 2020 dataset+Br35H MRI dataset)	Managing tumor heterogeneity and the lack of high-quality annotated data are two obstacles. Integrating multimodal imaging data and creating interpretable,
[10]	GAN	-	The main limitation in validation is the lack of sufficient MRSI data acquired at high resolution
[11]	Real Enhanced Super-Resolution GAN (Real-ESRGAN)	four distinct medical image types: 1) brain MRI images from the BraTS; 2) Dermoscopy images from ISIC skin cancer dataset; 3) cardiac ultrasound	1) generalization to diverse medical modalities++ 2) computational complexity++3) training data limitations ++4) clinical adoption
[27]	AmbientGANs, ProGAN, ProAmGAN, and Sty2AmGAN models	Alzheimer’s Disease Neuroimaging Initiative (ADNI) database	It is desirable to establish SOMs from experimental imaging measurements acquired by use of a well-characterized imaging system.

Fig.8 illustrates the available datasets and the frequency of their use by researchers. Each specific dataset is collected based on different criteria and is used for Brain Cancer. Due to the sensitivity of the data, it was noted in the majority of studies that models were developed based on the Kaggle BraTS DB, which is used for brain tumor segmentation, classification and enhancement of tumor types, and sometimes predicting patient outcomes (such as survival). However, some studies relied on real data while maintaining confidentiality and patient privacy.

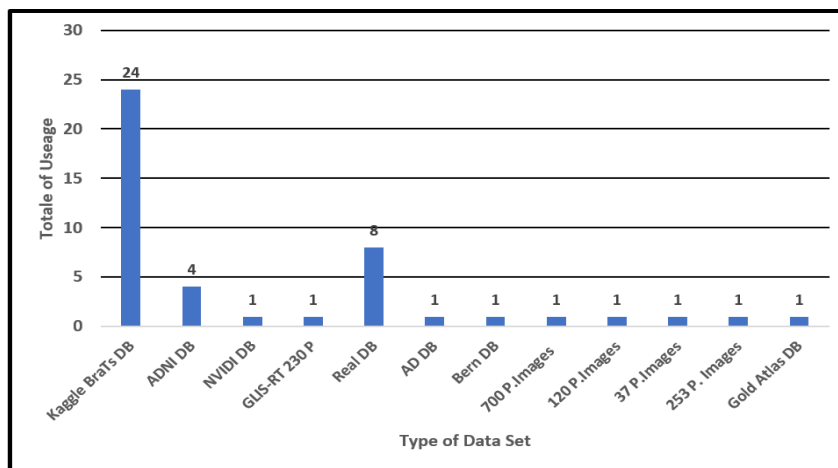


Figure 8. The use of various datasets in Brain and Glioma Diseases studies.

Whereas Fig.9 shows the frequently used evaluation metrics in Brain Cancer researches such as: Peak signal-to-noise ratio (PSNR); Structural Similarity Index Measure (SSIM); Root Mean Square Error (RMSE); Mean Absolute Error (MAE); Mean Square Error (MSE); Dice Similarity Coefficient (DSC); Intersection over Union (IoU); Normalized Root Mean Square Error (NRMSE); Mean Squared Information Score (MSIS); Variance Inflation Factor (VIF); Random Forest Spatiotemporal Model (RFSTM); Fréchet Inception Distance (FID); Learned Perceptual Image Patch Similarity (LPIPS); Pearson Correlation Coefficient (PCC); and finally, Noise Quality Measure (NQM). The best metric used to compare studies' results is PSNR, which is used to evaluate the quality of images after compression or modification, by comparing the original image to the resulting image. The higher PSNR value, the greater the similarity between the two images (i.e., better quality).

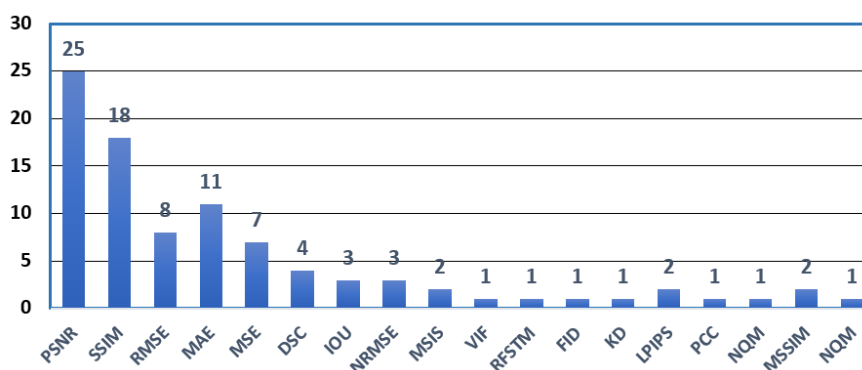


Figure 9. Frequently used evaluation metrics in Brain cancer Researches

The metric SSIM is used to compare the similarity of two images in terms of structure instead of just comparing pixels, and it is widely used in image processing, evaluating image quality after transmission; and comparing an original image with a reconstructed image. The metric RMSE is used to measure the accuracy of statistical models, it calculates the difference between predicted values and actual values. Whereas metric MAE is used to evaluate how accurate the model is by calculating the average absolute differences between actual and predicted values. This shows the average amount of error without considering the direction of the error (negative or positive). If you are working on evaluating a model, many studies have used SSIM with MSE and PSNR because MSE and PSNR only measure numerical differences, while SSIM tries to mimic the way humans perceive differences between images.

However, some studies have used other metrics: DSC, which is used to assess the similarity between two groups and is often used in medical image analysis (comparing automatically segmented areas with manually corrected areas). The IoU metric, has been used to evaluate the accuracy of models in object detection tasks, measures how well the predicted bounding box matches the ground truth box. And NRMSE metric has been used to measure the accuracy of the model in prediction, and it is considered a modified version of RMSE where the value is normalized to be more comparable across different datasets. RMSE is normalized by dividing it by the range or the mean of the original data. It is considered better

than RMSE because RMSE measures the amount of error absolutely, while NRMSE reflects the error relative to the range or mean of data, making it more comparable across different datasets.

From the above, we can use PSNR if we want a simple mathematical metric, or use SSIM to assess images as they are perceived by humans. We prefer to use NQM if we need a precise evaluation of image quality from a neuro-visual perspective (especially in medical sensitive applications). Perceptual metrics such as SSIM, MS-SSIM, VIF, LPIPS, and NQM reflect perceived visual quality better than traditional metrics like PSNR and MSE. It is preferable to use DSC and IoU in image segmentation to evaluate the extent of overlap between predicted and actual areas, and it is recommended to use FID and LPIPS in evaluating AI-generated images in GAN.

6. Recommendations

The study presented a detailed overview of GAN DL approaches in Brain Tumors diagnosis and their generative capabilities for medical imaging data, different loss functions for G and D, or the combination of multiple loss functions to improve performance, as well as their challenges they faced. From our reading, many challenges in Brain Tumor detection systems using GANs:

- Concerns regarding biological effects: Slight pixel variation; Low image resolution; Physiologically large discs; Presence of coexisting diseases; and Variation in Glioma.
- Reliability concerns: such as Ground truth reliability; Segmentation accuracy; Sparse annotations; and Unauthorized AI software.
- Deep Learning concerns such as: Small Dataset size; and computational time issues.
- Regarding GAN techniques: Optimization problems; Lack of standardized architecture; Overfitting; and Evaluation metrics.
- Concerns related to availability and services such as: Lack of experts; Lack of annotated images; Time required for annotation; Patient privacy; Imbalanced datasets; and Limited image diversity.

According to our analysis to literature related studies, we advise to adopt the following recommendations to improve GAN DL approaches used for early Brain Tumor Diagnosis systems:

6.1 Image Preprocess/Postprocess Algorithms

It is important to use qualified image preprocessing and postprocessing algorithms to obtain accurate and efficient results. Preprocessing algorithms prepare raw image data for further analysis. This involves:

- Normalization to adjust pixel intensity values to a standard range 0–255 or 0–1.
- Resizing and cropping to ensure consistent input dimensions for GAN DL models.
- Color Space Conversion to convert between Grayscale, RGB, etc.
- Noise Reduction: Gaussian Blur that smooths the image to reduce high-frequency noise. And Median Filtering to remove salt-and-pepper noise while preserving edges.
- Contrast Enhancement: Histogram Equalization to improve contrast by spreading out intensity values.

Whereas image postprocessing algorithms used to refine the output of image analysis or enhancement tasks and extract final results. This involves:

- Morphological Operations (Dilation, Opening, Closing) to clean up binary masks or segmentations.
- Image Reconstruction to combines processed image parts or corrects distortions.
- Segmentation Refinement (Watershed) to improve object boundaries in segmented images.
- Filtering and Smoothing to removes artifacts or enhances visual appeal after processing.

6.2 Enhanced Functions of GAN Deep Learning

We advise to use one or more of the several advanced techniques that improve stability, performance and output quality of GAN DL functions:

- Conditional GANs (cGANs) by adding conditions to both generator and discriminator. It is useful for generating specific categories.
- CycleGAN: To enable image-to-image translation without paired data.

- Attention GANs: Integrate attention mechanisms to focus on important regions to enhance detail and realism in generated outputs.
- Progressive Growing GANs: Train GAN by gradually increasing image resolution to improve stability and quality for high-res image generation.
- BigGAN: Scales up GAN for large datasets and high fidelity but it requires significant computational resources.
- StyleGAN / StyleGAN2 / StyleGAN3: to introduce style-based generation for high-quality, controllable image synthesis. It is used in face generation, art creation, and more.
- Pix2Pix / Pix2PixHD: Supervised image-to-image translation using paired datasets. It is great for tasks like segmentation-to-image.

Also, we advise to use one or more of the following applications to enhance GANs

- Data Augmentation: Generating synthetic data to improve model training.
- Medical Image Synthesis: Creating realistic images from noise or enhancing scans for diagnostics.

6.3 Enhance GAN Discriminator for Training

The discriminator distinguishes between real and generated data and its impacts the generator's ability to improve GAN. Several strategies to enhance the GAN discriminator:

- Deeper Networks by adding more layers to allow the discriminator to learn complex features. The use of deeper GAN training would improve capturing more precise and complex features. Also, use residual connections by incorporating ResNet-style skip connections to improve gradient stability.
- Training techniques such as Label Smoothing by using soft labels (e.g., 0.9 for real, 0.1 for fake) Instead of using hard labels (0 or 1) to prevent overconfidence. The Gradient Penalty can be used in WGAN-GP to enforce Lipschitz continuity which stabilizes training. And apply One-sided Label Smoothing only to real labels to avoid weakening the discriminator too much.
- Loss Function Enhancements: by using Wasserstein Loss: Improves gradient quality and training stability compared to binary cross-entropy. Also, we can use Hinge Loss: Encourages the discriminator to be more confident in its decisions, often used in StyleGAN.
- Data Augmentation: either Differentiable Augmentation to apply augmentations like rotation, flipping, or color jittering directly to both real and fake images during training, or by using Adaptive Augmentation: Adjust augmentation strength based on discriminator performance to prevent overfitting.
- Multi-scale Discriminators: Use multiple discriminators operating at different image resolutions to capture both global and local features.
- Feature Matching: Instead of just using the final output, use intermediate features from the discriminator to guide the generator, promoting more realistic outputs.
- Balanced Training: Avoid overpowering the discriminator. If it becomes too strong, the generator may not learn effectively.

6.4 Sufficient Number of GAN Training Steps

- We advise to use a sufficient number of training steps to improve the GAN results. The number of GAN training steps depends on: Dataset size and complexity; GAN architecture (e.g., DCGAN, StyleGAN, CycleGAN) and Desired output Image quality.
- We advise to monitor GAN training Quality instead of setting a fixed number of steps. This is done by using Loss curves (Generator and Discriminator); the use of Visual inspection of generated samples; and use of IS (Inception Score)
- In order to improve GAN Training, we advise to: use progressive growing; Use spectral normalization or gradient penalty to stabilize training; Apply label smoothing and feature matching; and Try adaptive learning rates or two-time-scale update rule (TTUR)
- Save GAN model checkpoints periodically and evaluate them. Sometimes the best results occur before the final step due to overfitting or mode collapse.

6.5 Medical Knowledge in Brain Tumor

The GAN approaches designers and programmers should have a sufficient medical knowledge in Brain Tumor disease. This is important to:

- Understand Brain Tumor heterogeneous types and characteristics: This helps in: Differentiating between Gliomas, Metastases, and Meningiomas. It is also help in recognizing Brain Tumor boundaries, patterns, and Tissue characteristics in MRI scans.
- Data Annotation and Validation: Medical experts are essential for accurate labeling of MRI images. Images generated using GAN must be clinically plausible. This is because unrealistic images can compromise diagnostic accuracy.
- Avoiding Misdiagnosis Risks: Without medical oversight, GANs may generate anatomically incorrect images that lead to false positives/negatives in tumor detection, affecting patient outcomes.
- Ethical and Regulatory Compliance: Medical professionals help ensure that AI models comply with ethical guidelines, clinical standards and privacy laws.

7. Conclusions

Recent DL GANs techniques have shown encouraging performance in Brain Tumor disease detection. Although this methodology involves an extensive computing budget and optimization process, it saturates the greedy nature of deep learning techniques by synthesizing images and solves major medical issues. This work contributes to this research field by offering a comprehensive analysis of existing works, highlighting current limitations, and suggesting alternatives to support other researchers and strengthening the future work. Finally, according to our comparative analysis, the key challenges of the related studies were addressed.

Many recommendations associated with improving Deep Learning GAN approaches to achieve high-accuracy and early Brain Tumor diagnosis were addressed such as: using of qualified image preprocess and postprocess algorithms; Enhanced Functions of GAN Deep Learning; Enhance GAN Discriminator for GAN Training; Using sufficient number of GAN training steps; and Sufficient Medical Knowledge in Brain Tumor. In the future work we will adopt DL with more advanced versions of GANs that work better at generalizing features to improve resolution of MRI images of Brain Tumors diagnosis.

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Conflicts of Interest

The author declares no conflicts of interest.

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